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Monitoring the heart rate variability responses to training loads in competitive swimmers using a smartphone application and the Banister Impulse-Response model

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Abstract

Purpose: Firstly, to examine whether heart rate variability (HRV) responses can be modelled effectively via the Banister Impulse-Response model (IR) when the session rating of perceived exertion (sRPE) alone, and in combination with subjective well-being measures, are utilised. Secondly, to describe seasonal HRV responses and their associations with changes in critical speed (CS) in competitive swimmers. **Methods:** Ten highly-trained swimmers collected daily 1-min HRV recordings, sRPE training load, and subjective well-being scores via a novel smartphone application for 15-weeks. The IR model was used to describe chronic Root Mean Square of the Successive Differences (rMSSD) responses to training, with sRPE and subjective well-being measures used as systems inputs. Changes in CS were obtained from a 3-min all-out test completed in Week 1 and 14. **Results:** The level of agreement between predicted and actual HRV data was $R^2=0.66\pm0.25$ when sRPE alone was used. Model fits improved in the range of 4-21% when different subjective well-being measures were combined with sRPE, representing *trivial-to-moderate* improvements. There were no significant differences in weekly group Ln rMSSD_{MEAN} ($p=0.34$) or HRV coefficient of variation (Ln rMSSD_{CV}) ($p=0.12$), however, *small-to-large* changes ($d=0.21$ - 1.46) were observed in these parameters throughout the season. Large correlations were observed between seasonal changes in HRV measures and CS (Δ Ln rMSSD_{MEAN}: $r=0.51$, $p=0.13$; Δ Ln rMSSD_{CV}: $r=-0.68$, $p=0.03$). **Conclusion:** The IR model and data collected via a novel smartphone application can be used to model HRV responses to swimming training and non-training related stressors. Large relationships between seasonal changes in measured HRV parameters (especially Ln rMSSD_{CV}) and CS provide further evidence for incorporating a HRV-guided training approach.

Key words: heart rate variability, modelling, monitoring, training, swimming

Introduction

The overarching aim of coaches is to design training programmes that are effective and sustainable, with the ultimate goal being to allow athletes to achieve maximal performance when it matters the most. Our understanding of effectively managing training programmes of athletes has advanced^{1,2}, but sports practitioners and athletes still face the ever-lasting challenge of effectively monitoring and balancing the training stimulus and recovery whilst often operating under the constraints of limited resources and time.

A promising method to monitor athletes' adaptations to prescribed training involves monitoring of the cardiac autonomic nervous system, specifically its parasympathetic arm via the measurement of resting heart rate variability (HRV) and its day-to-day variation³. Indeed, HRV has been shown to be related to training load⁴⁻⁷, performance^{5,6}, health⁸ and psychological status of athletes^{4,9} in various sports including swimming. Consequently, HRV has become a promising candidate for monitoring global responses of athletes to training¹⁻⁴. Given this, Chalencon et al.⁶ explored the possibility of applying the Banister Impulse-Response (IR) model¹⁰ to describe the impact of training on nocturnal HRV measures in competitive swimmers over a 30-week period. The modelled HRV responses were compared with performance outcomes and Chalencon et al.⁶ not only showed excellent model fit to both HRV ($R^2=0.79\pm0.07$) and performance responses ($R^2=0.84\pm0.14$), but also observed strong positive correlations between the HRV and performance responses to training load. The authors consequently suggested that HRV may be used as a proxy to track the impact of training on athletes' fatigue and adaptation status without interfering with training programmes to collect performance measures. However, considering the methodology utilised by Chalencon et al.⁶, some potential issues can be raised regarding the accuracy and practical applicability of the methods. Specifically, the authors collected HRV only once per week and utilised the high-frequency (HF) component of HRV rather than averaging daily HRV measurements of the square root of the mean of the sum of the squares of differences between adjacent normal R-R intervals (rMSSD), which has been recommended and is a commonly used method in sports performance^{1,2}. Additionally, the need to purchase heart rate monitors, to collect nocturnal HRV data, and to calculate training load as suggested by the authors would be challenging for regular swimming teams that typically have a large number of swimmers and limited resources, time and/or expertise. In addition to this, whilst nocturnal HRV measurements utilised by Chalencon et al.⁶ may theoretically provide better HRV recordings due to reduced impact of environmental factors during sleep², there is also evidence that nocturnal measures do not capture the impact of psychological stress on HRV as well as morning measures, and therefore may not capture this important aspect of an athlete's status¹¹.

The recent development of affordable and easy-to-utilise smartphone technology has enabled the collection of daily HRV measurements, alongside measures of training load and subjective scores, in a valid and practically-feasible manner¹². Therefore, the primary aim of the present study was to examine whether the findings of Chalencon et al.⁶ could be replicated when daily and morning 1-min recordings of rMSSD HRV measure collected via a novel smartphone application and the session rating of perceived exertion as a training load measure (i.e., a method utilised by most coaches) are utilised in the IR model as outputs and inputs, respectively. In addition, given that non-training related stressors can impact on athlete's responses to training^{4,9}, measures of several subjective indicators of recovery status will be combined with sRPE in order to examine whether the ability to model HRV responses improves. Finally, as there is a lack of studies that have obtained daily measures of HRV in response to longer training periods, an additional aim of the present study was to monitor HRV

responses and their associations with changes in critical speed, as a performance-related measure, in a group of highly-trained swimmers over one short-course season.

Methods

Subjects

A group of twelve healthy and highly-trained swimmers from the same swimming team volunteered to participate in the present study. Ten swimmers were included in the final analysis as two swimmers were excluded from the present study due to lack of compliancy with the required HRV procedures (Table 1). Ethical approval was received from the Research Ethics Approval Committee for Health at the University of Bath, and the study was conducted in accordance with the Declaration of Helsinki.

Insert Table 1 here

Design

The present study is an extension of the study recently published by Piatrikova et al.,¹³ which examined physiological, performance and technical changes in response to a 15-week training programme. Briefly, swimmers were prescribed with individualised high-intensity interval training (HIIT) (3 times.week⁻¹) based on the critical speed (CS) and critical stroke rate (CSR) concepts, whilst overall training volume was reduced ($\geq 25\%$). The study period represented a short-course swimming season (September-December) and included periods of overload, recovery, an overseas training camp (~1400-km flight travel, 1-h time-zone loss), and taper, which also led into a key race of the season. In addition to the 3-min all-out tests (3MT) completed at the beginning of the study (week 1) and subsequently at the end of each training cycle (weeks 6, 11, 14), the swimmers were also asked to collect daily HRV, training load and subjective measures via a smartphone application that were subsequently utilised for the following purpose: 1) to model HRV responses to training load alone, or in combination with subjective well-being measures, using the IR model¹⁰; 2) to monitor week-to-week HRV responses of the swimmers to the designed 15-week programme; and 3) to examine relationships between changes (Δ) in HRV and CS measures elicited over the season (from week 1 to week 14). Any training advice and results given by the HRV application was hidden from the athletes and coaches in the present study.

Methodology

Heart rate variability

Swimmers were instructed to perform a 1-min HRV self-measurement each morning upon waking in a supine position. Photoplethysmography (PPG) was utilised to acquire HRV readings via a smartphone application (HRV4Training)¹². The rMSSD component of HRV was used in the present study due to its reliability and practicality¹. To examine seasonal HRV responses, the rMSSD data were first log-transformed (Ln) to reduce non-uniformity of error and weekly (7 days) averages of Ln rMSSD (Ln rMSSD_{MEAN}) as well as its coefficient of variation (Ln rMSSD_{CV} = [Ln rMSSD_{SD}/Ln rMSSD_{MEAN}] x 100) were calculated. A 42-day exponentially weighted average of raw rMSSD (rMSSD_{42-EXP}) was calculated using Equation 1 and was utilised in the IR model as a representative marker of chronic training adaptation¹⁴. The IR models were first run with raw rMSSD values and were subsequently compared to models utilising Ln rMSSD data. The raw rMSSD values provided a better overall model fit than Ln rMSSD (R^2 : 0.59 ± 0.37 vs 0.52 ± 0.39) and so raw rMSSD values were used for IR modelling. The rMSSD_{42-EXP} calculation was initiated with the mean rMSSD value observed across the first seven days of the monitoring period.

Equation 1

$$rMMSD\ EWMA_{today} = rMMSD_{today} \times \lambda_{\alpha} + ((1 - \lambda_{\alpha}) \times rMMSD\ EWMA_{yesterday})$$

$$\text{where } \lambda_{\alpha} = \frac{2}{42 + 1}$$

Training load

Upon completion of HRV measurement, the swimmers were asked to report their training load for the preceding day within the HRV4Training application. The athletes were asked to provide an intensity score (Borg CR-10 scale) and duration (minutes) of their previous day's training sessions, which were subsequently multiplied to calculate a daily sRPE score in arbitrary units (A.U.)¹⁵.

Subjective well-being scores

The psychometrics were recorded daily and immediately following HRV recordings via the HRV4Training application. The swimmers were asked to subjectively rate their sleep quality, lifestyle stress, motivation, mental energy, fatigue and muscle soreness on a scale which was assigned with a 1-100 score by the application.

The Banister Impulse-Response model

The mathematical relationship between training loads (system input) and rMSSD_{42-EXP} (system output) was modelled for each athlete via the two-component IR model¹⁰. This model is characterized by two gain terms (k_1 and k_2) and two time constants (τ_1 and τ_2) for the positive (adaptation) and negative (fatigue) component, respectively, and an initial performance level (p) which was represented by HRV:

$$\hat{p}^n = p^* + k_1 \sum_{i=1}^{n-1} w^i e^{-(n-i)/\tau_1} - k_2 \sum_{i=1}^{n-1} w^i e^{-(n-i)/\tau_2}$$

Additional terms were linearly added on to this model to incorporate subjective well-being data as an additional input. The model parameters were determined by minimising the Sum of Squares Error (SSE) between estimated and measured rMSSD_{42-EXP} using the *dorem* package in R Studio (RStudio, Inc., Boston, USA) designed by Jovanovic and Hemingway¹⁶ and a customised spreadsheet based on Clarke and Skiba¹⁷, which provides a step-by-step procedure for fitting the IR model using the Solver function in Excel.

Critical speed

To assess the relationships between change in the HRV parameters and performance-related measure during the investigated period, ΔCS was established from the 3MT completed by swimmers in weeks 1 and 14. CS was chosen as it represents both a valuable performance and physiological variable¹³.

Statistical analysis

The data are presented as means, standard deviations (SD) and 95% confidence limits. To evaluate changes in Ln rMSSD_{MEAN} and Ln rMSSD_{CV} throughout the season, one-way repeated measures ANOVA and effect size statistics were utilised. Standardised differences in mean values were calculated using thresholds described by Hopkins et al.¹⁸, where 0-0.2 was *trivial*, 0.2-0.6 was *small*, 0.6-1.2 was *moderate*, 1.2-2.0 was *large*, 2.0-4.0 was *very large*, and >4.0

was *extremely large*. A bivariate Pearson correlation was utilised to assess relationships between $\Delta \text{Ln rMSSD}_{\text{MEAN}}$ and $\Delta \text{Ln rMSSD}_{\text{CV}}$ and ΔCS from week 1 to 14. Default correlation thresholds were 0.1, small; 0.3, moderate; 0.5, large; 0.7, very large; 0.9, nearly perfect¹⁹. To assess differences between the IR model fit (R^2) to actual $\text{rMSSD}_{42\text{-EXP}}$ data when sRPE was combined with different subjective scores as opposed to sRPE only, standardised differences and paired samples t-tests or the Wilcoxon signed-rank test were used. The Wilcoxon signed-rank test was performed on data showing non-normality. Statistical significance was set at $p < 0.05$.

Results

Weekly HRV responses

The changes in average weekly $\text{Ln rMSSD}_{\text{MEAN}}$ and $\text{Ln rMSSD}_{\text{CV}}$ along with average weekly sum of sRPE are illustrated in Figure 1. There were no statistically significant differences between weekly $\text{Ln rMSSD}_{\text{MEAN}}$ ($F_{(4.85, 43.64)} = 1.17, p = 0.34$) or weekly $\text{Ln rMSSD}_{\text{CV}}$ ($F_{(5.29, 47.57)} = 1.86, p = 0.12$), however, *small-to-large* effect size changes were observed.

Insert Figure 1 here

Correlations between seasonal changes in HRV and CS

There was a large but non-significant correlation between $\Delta \text{Ln rMSSD}_{\text{MEAN}}$ vs ΔCS ($r = 0.51; p = 0.13$), whilst the correlation between $\Delta \text{Ln rMSSD}_{\text{CV}}$ and ΔCS was large and significant ($r = -0.68, p = 0.03$) (Figure 2).

Insert Figure 2 here

Modelling HRV using sRPE

The mean and individual swimmers' values of the gain and time delay constants, and p are illustrated in Table 2. Figures 3-5 illustrate model fit to actual $\text{rMSSD}_{42\text{-EXP}}$ data in individual swimmers when sRPE was used as the system's input. The IR model produced high goodness-of-fit (R^2) to $\text{rMSSD}_{42\text{-EXP}}$ (mean \pm SD: $R^2 = 0.66 \pm 0.25$; $\text{SSE} = 2278 \pm 2025$ ms), with individual R^2 values ranging from 0.21 to 0.98.

Insert Table 2 here

Modelling HRV using sRPE and subjective well-being scores

Mean R^2 improvements in the range of 4-21%, representing *trivial-to-moderate* effects, were observed when sRPE was combined with one of the subjective *well-being* measures (Table 3). Only addition of mental energy and motivation score to sRPE resulted in statistically significant improvement in the model fit. Additionally, combination of sRPE with the subjective parameter which resulted in the best model fit within individual swimmers resulted in statistically significant improvement in the model fit. Figures 3-5 illustrate a model fit improvement when sRPE and the best subjective *well-being* measure for each individual were combined.

Insert Figures 3-5 here

Insert Table 3 here

Discussion

The principal finding of the present study is that HRV can be modelled effectively using an Impulse-Response model and sRPE. Additionally, when sRPE was combined with different subjective *well-being* measures as the system's input, the fit of the model to the HRV data

improved in the range of 4-21%, representing *trivial-to-moderate* improvements. Finally, although changes in $\text{Ln rMSSD}_{\text{MEAN}}$ and $\text{Ln rMSSD}_{\text{CV}}$ were statistically non-significant, *small-to-large* changes were observed in these parameters throughout the season, with $\text{Ln rMSSD}_{\text{CV}}$ appearing more sensitive to changes in training programme. When the seasonal changes in the HRV measures were related to the corresponding changes in CS, large correlations were observed, indicating that athletes who experienced larger increases in $\text{Ln rMSSD}_{\text{MEAN}}$ and decreases in $\text{Ln rMSSD}_{\text{CV}}$ achieved greater improvements in CS.

A high goodness-of-fit between predicted and actual $\text{rMSSD}_{42\text{-EXP}}$ ($R^2=0.66\pm0.25$) was observed in the present study. This is, however, numerically lower compared to the findings of Chalencon et al.⁶ who observed an R^2 of 0.79 ± 0.07 . This is somewhat surprising considering that the HRV methods utilised in the present study were arguably more valid^{1,2,11}. The lower model fit could, however, be attributed to taking morning measures as opposed to nocturnal, which tend to be affected by psychological stress to greater extent than nocturnal measures¹¹. Alternatively, the lower model fit might be related to the data utilised as the system's input. Chalencon et al.⁶ calculated training load as the sum of pool-kilometres swum and the dry-land workout equivalent, which were exponentially weighted according to seven intensities. The present study used sRPE, which is considered to be a valid method of calculating training load²⁰, however, it may be that this approach was not able to capture the training load as effectively. Nonetheless, it is important to note that one of the main aims of this study was to explore whether a simpler method can be used to model HRV. Indeed, when **subjective well-being** scores were combined with sRPE as the model's input, the accuracy of the model improved substantially, and matched or exceeded the model fit observed by Chalencon et al.⁶. As illustrated in figures 3-5, the magnitude of model fit improvement is likely athlete-dependant and provides further evidence for incorporating multiple measures when modelling responses to training²¹.

There was no statistically significant change in $\text{Ln rMSSD}_{\text{MEAN}}$, despite the programme including periods of overload, taper and travelling, which have been shown to influence HRV^{1,4,5,22}. Our results are in contrast with studies of Garet et al.⁵ and Flatt, Hornikel and Esco⁴, who observed significantly reduced HRV during an overload period, which either peaked or returned to baseline values during the taper in competitive swimmers. Importantly, both Garet et al.⁵ and Flatt, Hornikel and Esco⁴ established 'baseline' HRV values from the week preceding the overload period, whilst the baseline in the present study was collected in week 1. Indeed, whilst not statistically significant, there was a *small* reduction in $\text{Ln rMSSD}_{\text{MEAN}}$ during the training camp, after which $\text{Ln rMSSD}_{\text{MEAN}}$ changed only *trivially*. When assessed on an individual basis, however, substantial inter-subject variability was evident (Figures 3-5). This along with three swimmers **not attending** the camp could therefore explain why changes in $\text{Ln rMSSD}_{\text{MEAN}}$ were non-significant and mostly trivial when assessed on a group level. Stable or increasing HRV generally indicates athletes are coping well with training, whilst decreasing HRV could be indicative of athlete's inability to adapt to designed training/increased stress. Although training sessions were prescribed in an individualised manner¹³, differences in the swimmers' HRV responses provide evidence that some athletes responded to the prescribed training more favourably than the others. Indeed, Vesterinen et al.²³ showed that initial HRV values should be considered when designing training programme for individual athletes, as the athletes who had higher baseline HRV benefited more from the higher intensity programme than athletes with lower baseline HRV. Alternatively, the timing of an overload period or HIIT appears important and should ideally coincide with the time when athletes' HRV is stable or trending positively²⁴⁻²⁵. Given that this was not considered in this study, as is often the case in applied practice, scheduling of HIIT and an overload period may have not been optimal in some athletes.

Changes in $\text{Ln rMSSD}_{\text{CV}}$ were also statistically non-significant, although $\text{Ln rMSSD}_{\text{CV}}$ appeared more sensitive to changes in training programme. Specifically, after the first two weeks of training intervention, there was a *small* reduction in $\text{Ln rMSSD}_{\text{CV}}$ from week 3 to 4. This remained stable and below baseline values until commencement of an overseas training camp where a *moderate* increase in $\text{Ln rMSSD}_{\text{CV}}$ was observed. Once swimmers returned to normal training schedule, *small* week-to-week reductions in $\text{Ln rMSSD}_{\text{CV}}$ were observed up to the start of week 13 (“stress/illness” week). In this week a *moderate* increase in $\text{Ln rMSSD}_{\text{CV}}$ was observed, however, this was reversed during the taper, where $\text{Ln rMSSD}_{\text{CV}}$ declined *moderately*. Following taper, week 15 (i.e., competition week) was characterised by a *large* increase in $\text{Ln rMSSD}_{\text{CV}}$. Our results are somewhat in agreement with Flatt, Hornikel and Esco⁴ who observed significantly greater $\text{Ln rMSSD}_{\text{CV}}$ during a 2-week overload period compared to the week preceding this period (6.7% vs. 10.1%; *moderate* increase), which returned to baseline values during subsequent 2-week taper. Given that $\text{Ln rMSSD}_{\text{CV}}$ is believed to represent the fatigue-recovery processes³⁻⁴, the following suggestions could be made based on the observed results: 1) the reduction of $\text{Ln rMSSD}_{\text{CV}}$ from week 3-4 and maintenance of reduced values up to week 7 could be indicative of positive responses to the designed programme³; 2) the increase in $\text{Ln rMSSD}_{\text{CV}}$ during the overseas camp could be indicative of greater stress and decreased ability to cope with designed training, probably due to increased amount of training as well as differences between training environments^{4,22}; 3) upon return to normal training schedule, $\text{Ln rMSSD}_{\text{CV}}$ continuously declined indicating improved ability to cope with the training until week 13; 4) despite week 13 being a normal training week, increased $\text{Ln rMSSD}_{\text{CV}}$ could be explained by non-training related stress or illness experienced by the majority of swimmers⁸⁻⁹; 5) this was subsequently reversed during the taper, where the window of opportunity for physical and mental recovery was greater; 6) a *large* increase in $\text{Ln rMSSD}_{\text{CV}}$ in week 15 could be attributed to travelling, increased anxiety levels associated with key competition, and racing multiple times during the day over several days.

The analysis of the relationships between ΔHRV indices and ΔCS revealed large correlations. Our findings are in agreement with Flatt and Esco³, who observed that a greater decrease in $\text{Ln rMSSD}_{\text{CV}}$ ($r=-0.74$) and increase in $\text{Ln rMSSD}_{\text{MEAN}}$ ($r=0.50$) within the first 3 weeks of training period were related to greater improvements in YoYo testing. However, Plews et al.²⁶ observed greater correlations between $\Delta\text{Ln rMSSD}_{\text{MEAN}}$ and $\Delta 10 \text{ km TT}$ ($r=-0.76$) and $\Delta\text{maximal aerobic speed}$ ($r=0.72$) after 9-week training. The differences could be related to the performance outcomes utilised to assess this relationship. Whilst CS is a performance-related measure, this parameter represents a sub-maximal intensity/threshold, and so HRV may have a stronger relationship with measures which represent athlete’s maximal capacity. Despite this, the findings of this study provide further evidence for utilising HRV-guided approach to optimise training outcomes, which has been shown to elicit smaller day-to-day HRV variation and superior adaptations when compared to non-guided, predefined training programmes²⁴⁻²⁵.

This study has some limitations that must be highlighted. There was a lack of direct performance measurements, which prevented us from examining relationships between HRV and performance responses. In addition to this, the R-code that was utilised to combine sRPE and subjective well-being measures to model HRV did not work in some participants due to an unexplained error with the optimisation function, which prevented us from making recommendations as to which subjective well-being measure improved the model-fit to the greatest extent. For coaches, the HRV4Training application provides correlations between individuals’ HRV metrics and their subjective well-being measures, which could be used to determine which well-being measure is most relevant for each athlete. The relatively small cohort used in this study hindered our ability to detect group-level differences and correlations in outcome measures. Finally, although the swimmers undertook a familiarisation with the app

prior to the study, and all data were revised every morning, we did not directly supervise each swimmer in order to replicate an applied environment. Therefore, some swimmers might have not recorded training load, subjective well-being and/or HRV data optimally on some occasions.

Practical applications

This study showed that HRV can be modelled effectively when simple methods such as sRPE and subjective well-being scores are combined in the IR model. Given that HRV is related to performance⁶, the inclusion of HRV could reduce the burden of repetitive performance testing, which currently limits the use of this model for monitoring and planning the training process. Coaches and athletes often operate with limited resources and time, and so the approach used is feasible to collect these data on a daily basis without compromising on validity. Although we did not examine the effect of a HRV-guided programme on swimming, the results from this study provide some evidence for utilisation of this approach in swimming training, given the relationships we observed between HRV indices and CS, as well as between-swimmer differences in HRV responses. Given that the role of the coach is to provide athletes with a programme that allows individuals to maximise their potential, HRV and subjective well-being measures could allow coaches to take the principle of individualisation a step further. Specifically, as demonstrated by previous studies²⁴⁻²⁵, HRV monitoring can assist coaches with decision making related to planning and optimal timing of HIIT sessions or intensive training blocks, which are typically standardised and prescribed subjectively in most swimming clubs. Alternatively, given that these monitoring systems collect data related to individual's recovery processes too, the combination of this data with training load and HRV can now assist practitioners with making more informed decisions as to what steps are required to optimise individual's HRV status, rather than opting for reduction in training as typically done.

Conclusion

In conclusion, the results from the present study demonstrate that HRV can be modelled with good accuracy when simple methods such as sRPE and HRV collected via a smartphone application are utilised in the Impulse-Response model. The accuracy to model the HRV improved meaningfully when subjective well-being measures were added into the model, suggesting the use of multiple variables when modelling HRV. Whilst there were no statistically significant differences in weekly Ln rMSSD_{MEAN} or Ln rMSSD_{CV}, small-to-large effects were observed in these parameters throughout the season, with Ln rMSSD_{CV} appearing more sensitive to changes in training programme than Ln rMSSD_{MEAN}. Finally, seasonal changes in the investigated HRV parameters were related to seasonal changes in CS, providing further evidence for incorporating HRV-guided training approach to facilitate optimal training prescription in individual swimmers.

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Figure captions

Figure 1. Mean $\text{Ln rMSSD}_{\text{MEAN}}$ and $\text{Ln rMSSD}_{\text{CV}}$ responses and weekly average sum of the sRPE for the 15-week period. Grey shaded area represents the smallest worthwhile change. *S*, *M* and *L* refer to *small*, *moderate* and *large* effect sizes, respectively. The effect size values reported below and above the “line of mean responses”, represent consecutive week-to-week changes and changes from baseline (week 1) values, respectively. Error bars represent 95% confidence limits for $\text{Ln rMSSD}_{\text{MEAN}}$ and $\text{Ln rMSSD}_{\text{CV}}$ and standard deviations for sRPE. Stress/illness refers to a week when majority of swimmers (i.e. six swimmers) experienced non-training related stress and/or illness.

Figure 2. Relationships between seasonal changes (Δ) in critical speed (CS) and heart rate variability measures of $\text{Ln rMSSD}_{\text{MEAN}}$ (A) and $\Delta \text{Ln rMSSD}_{\text{CV}}$ (B) ($n=10$).

Figure 3. Modelling HRV responses using sRPE alone and in combination with the best subjective well-being score in the swimmers 1-4.

Figure 4. Modelling HRV responses using sRPE alone and in combination with the best subjective well-being score in the swimmers 5-8.

Figure 5. Modelling HRV responses using sRPE alone and in combination with the best subjective well-being score in the swimmers 9-10.

452 **Table captions**

453 **Table 1.** General and performance characteristics of the swimmers.

454 **Table 2.** Estimates of model parameters using the Banister model.

455 **Table 3.** Comparison of the model fit (R^2) when sRPE in combination with subjective well-
456 being scores is used to model HRV responses.

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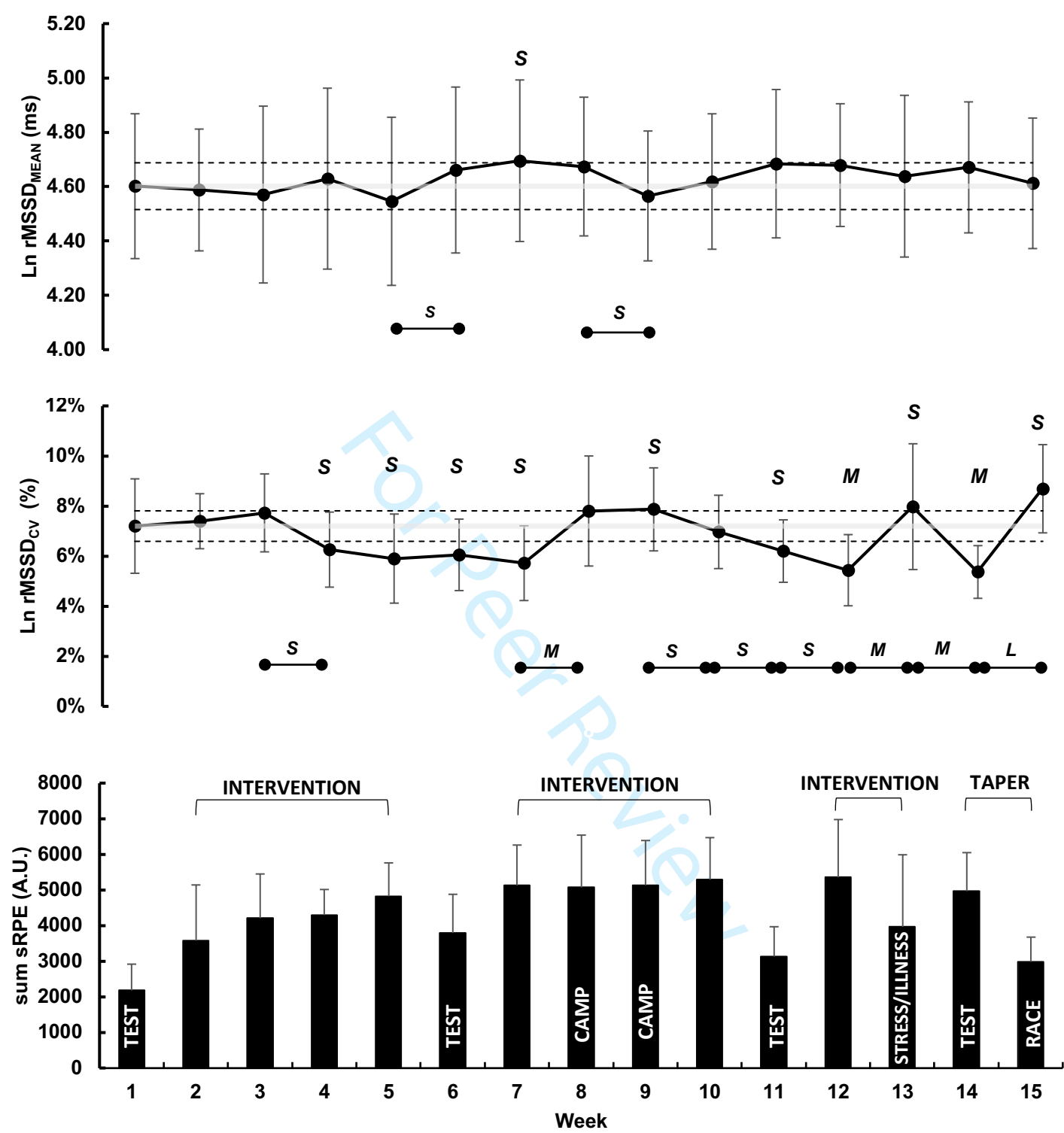


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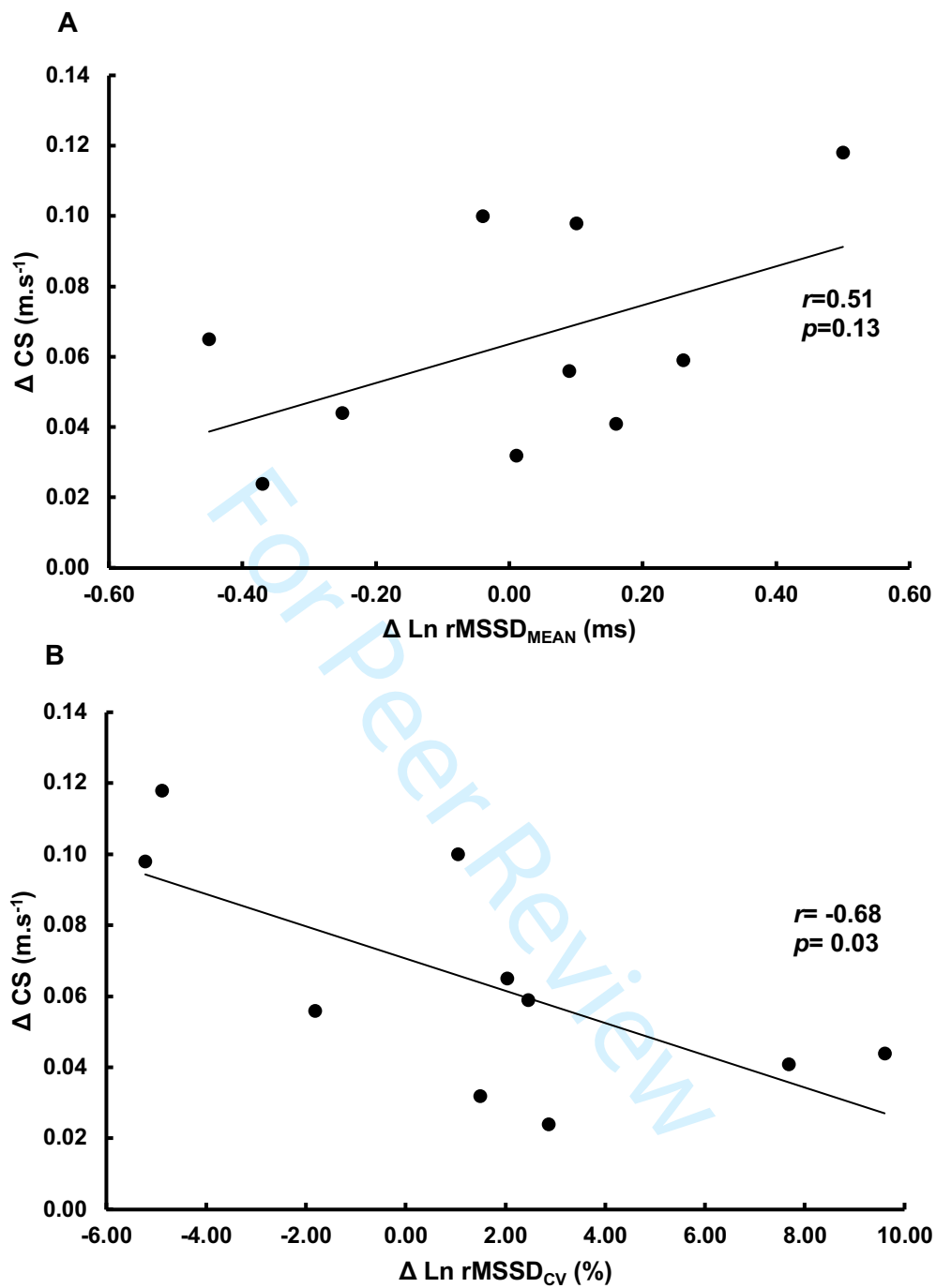


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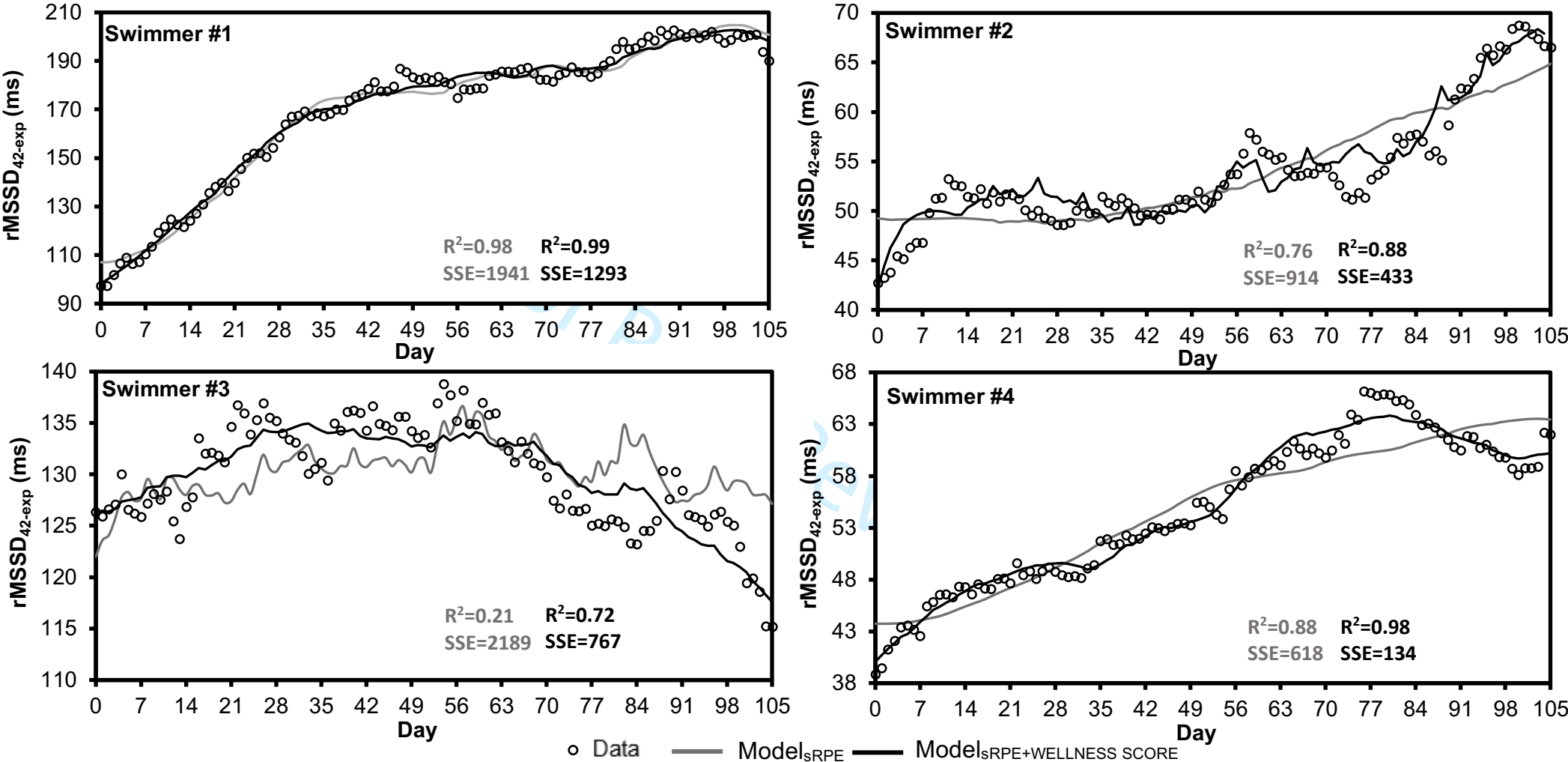


Figure 3. Modelling HRV responses using sRPE alone and in combination with the best subjective wellness score in the swimmers 1-4. Best subjective wellness score for swimmer 1: muscle soreness, swimmer 2-3: motivation, swimmer 4: life-stress.

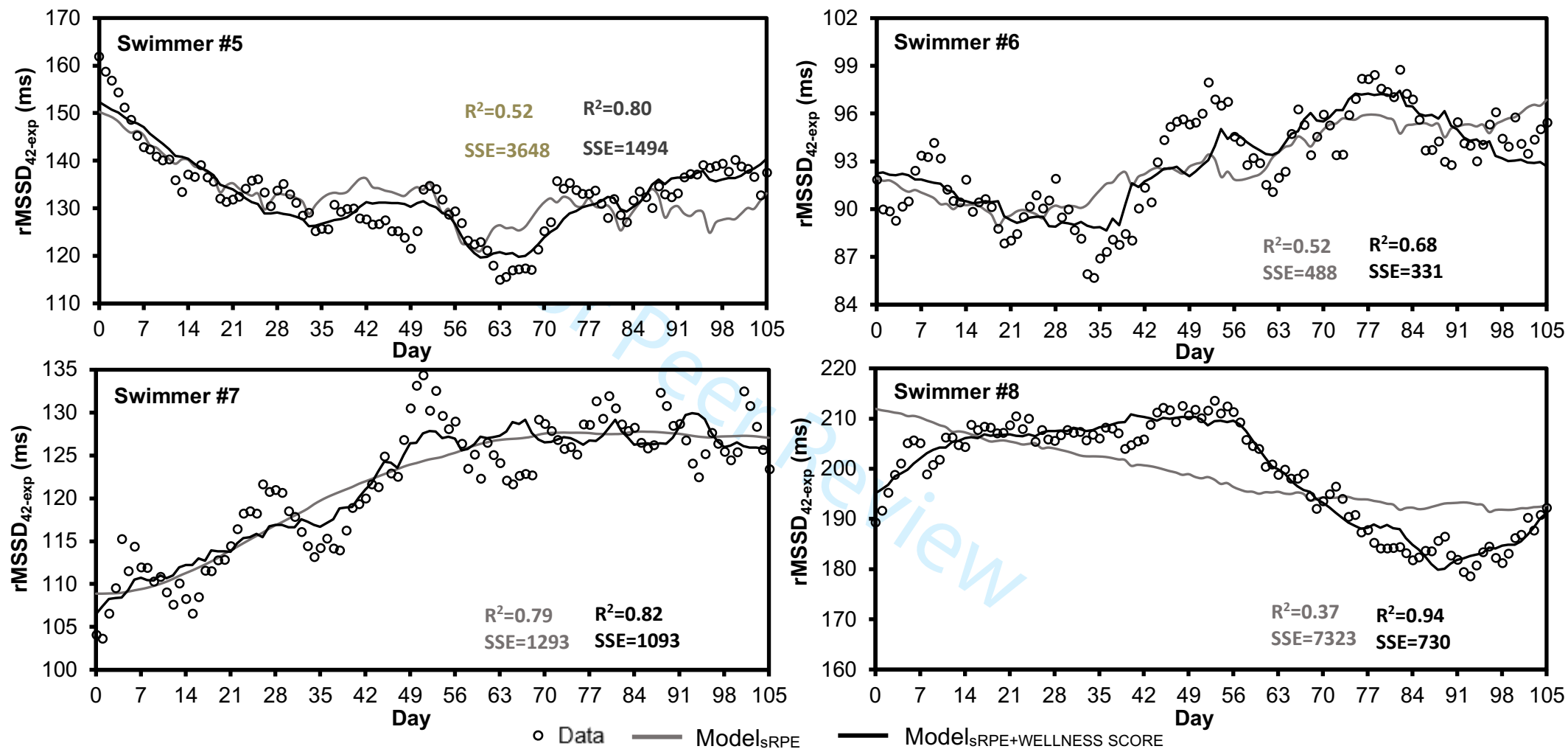


Figure 4. Modelling HRV responses using sRPE alone and in combination with the best subjective wellness score in the swimmers 5-8. Best subjective wellness score for swimmer 5 and 7: fatigue; swimmer 6: life-stress; swimmer 8: mental energy.

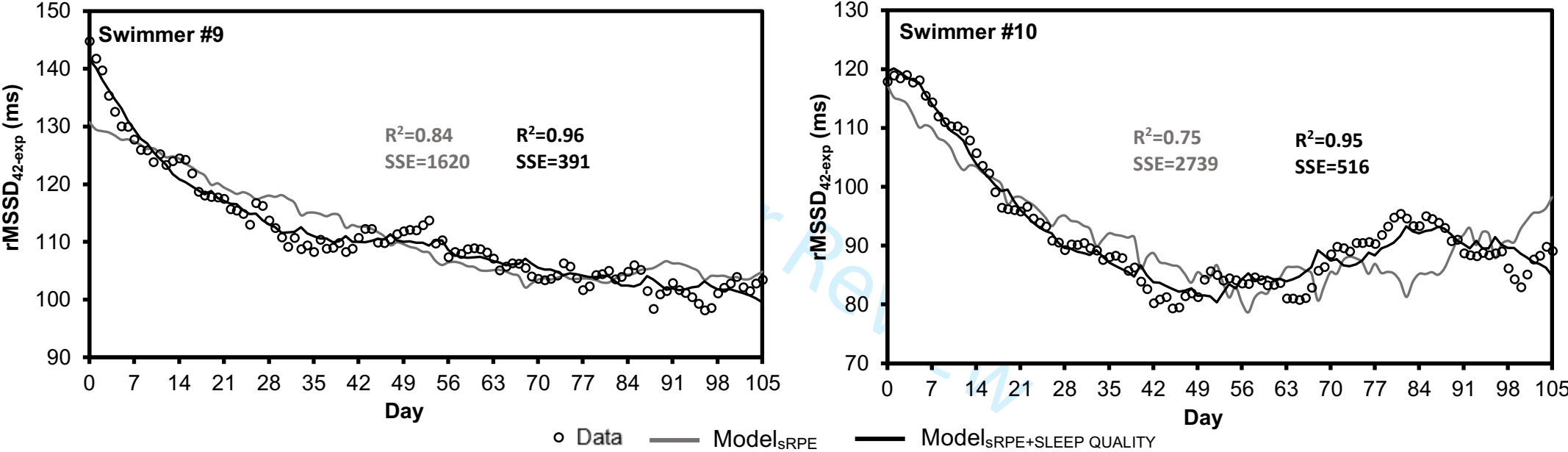


Figure 5. Modelling HRV responses using sRPE alone and in combination with the best subjective wellness score in the swimmers 9-10.

Table 1. General and performance characteristics of the swimmers.

Subject	Sex	Age (y)	Height (cm)	Weight (kg)	Training age (y)	1 st and 2 nd main event	1 st Main event PB (% WR)*
S1	M	15	184	71	7	100 m; 200 m butterfly	82%
S2	F	15	177	65	7	200 m, 100 m backstroke	86%
S3	F	17	180	77	7	100 m; 200 m freestyle	85%
S4	M	14	180	59	6	200 m, 100 m backstroke	78%
S5	M	16	180	70	6	200 m; 100 m freestyle	81%
S6	F	15	165	57	8	100 m; 200 m butterfly	81%
S7	M	16	180	67	8	200 m; 100 m freestyle	79%
S8	M	17	182	73	10	100 m; 200 m backstroke	83%
S9	M	15	178	59	5	100 m; 200 m breaststroke	82%
S10	F	17	163	53	8	200 m; 100 m freestyle	90%
Mean		16	177	65	7		83%
SD ±		1	7	8	1		4%

*Current world record (WR) for a short course (25 m) pool in the given event. Training age, training history; PB, personal best.

Table 2. Estimates of model parameters using the Banister model.

Swimmer	p (ms)	k_1 (AU)	k_2 (AU)	τ_1 (days)	τ_2 (days)
S1	107	0.064	0.064	12.09	9.92
S2	49	0.038	0.038	60.00	58.07
S3	122	0.006	0.003	5.19	4.00
S4	44	0.047	0.047	25.08	24.35
S5	150	0.049	0.052	11.51	11.50
S6	92	0.006	0.006	22.26	19.01
S7	109	0.010	0.010	19.01	16.21
S8	212	0.017	0.017	60.00	59.90
S9	131	0.031	0.032	44.19	44.10
S10	117	0.007	0.009	36.93	28.88
Mean	113	0.027	0.028	29.63	27.59
SD	48	0.021	0.022	19.81	19.97

p , initial level of $rMSSD_{42-EXP}$ component of HRV; k_1 and k_2 , multiplying factors for the positive and negative component of HRV, respectively; τ_1 and τ_2 : time constants of decay for positive and negative components of HRV, respectively.

Table 3. Comparison of the model fit (R^2) when sRPE in combination with wellness scores is used to model HRV responses.

Subjective wellness parameter	Model fit - R^2 (%)			<i>p</i>	Effect size
	sRPE only	Combined model	Improvement		
Life stress (n=7)	64±28	79±16	15±18	0.07	0.64 (moderate)
Mental energy (n=9)	64±25	80±21	16±17	0.01	0.67 (moderate)
Motivation (n=10)	66±25	82±17	16±20	0.01	0.77 (moderate)
Sleep quality (n=8)	72±24	75±30	4±11	0.12	0.13 (trivial)
Fatigue (n=7)	72±21	79±17	7±23	0.18	0.37 (small)
Muscle soreness (n=7)	68±28	87±9	19±24	0.09	0.91 (moderate)
Individuals' best marker (n=10)	66±25	87±11	21±19	0.01	1.10 (moderate)